Received: July 5, 2024. Revised: July 31, 2024.

International Journal of
Intelligent Engineering & Systems

http://www.inass.org/

Leveraging Generative Large Language Models for Optimizing Sales Arguments Creation: An Evaluation of GPT-4 Capabilities

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Abstract: A new era in Generative Artificial Intelligence has begun with the release of powerful Large Language Models (LLMs). These models have shown significant potential in marketing. Essentially, they have been redefining sales practices and changing sales funnel steps. Despite their promise and persuasive capabilities, there remains a dearth of comprehensive understanding regarding the capabilities of LLMs in generating sales arguments, which is a task traditionally characterized by high costs, time consumption, subjective biases, and the need for considerable expertise and skills. In this study, we take the first step towards exploring the ability of LLMs to generate sales arguments. To this end, we evaluated GPT-4 as one of the most capable LLMs to date in performing zero-shot sales argument creation from product features. We created a dataset containing textual descriptions of features extracted from brochures, catalogs, and technical data sheets of various products of a global company specializing in the manufacturing and retailing of furniture, appliances, and home accessories. We conducted a human evaluation with five experts, covering three main criteria of argument quality, namely coherence, persuasiveness, and relevance. The experimental results revealed the remarkable ability of GPT-4 to generate high-quality and well-structured sales arguments according to the Feature-Advantage-Benefit method. Over 98% of the evaluated arguments were coherent and persuasive. Regarding relevance, the model exhibited an accuracy of 91.53% to align the generated arguments to customers' purchase motives, namely security, vanity, novelty, comfort, money, and likability. These findings could lead to significant time and cost reductions, allowing the sales force to focus on higher-value tasks. We posit that this study heralds a novel avenue for exploring LLMs' capabilities in other steps of the sales funnel process.

Keywords: Sales argument, Feature-advantage-benefit method, Purchase motives, Large language models, GPT-4, Sales force, Persuasion, Efficiency.

1. Introduction

The advent of Marketing 4.0 has provided businesses with new opportunities for innovation and creativity in their business practices. Companies are investing significantly in sales technologies, such as digital tools and artificial intelligence (AI), to manage the sales process more efficiently [1, 2]. Sales, like any other function of a company, is experiencing the effects of AI [3, 4]. AI has been redefining sales practices at a rapid pace, changing all sales funnel steps [2, 5]. Sales offer presentation and customer objection handling are two key steps requiring the creation of a well-prepared sales argument. This latter task is complex due to the challenges associated with comprehending and addressing the diverse needs of each potential buyer [6]. Therefore, the sales force must engage in extensive preparation, which is the most time-intensive phase of the overall sales funnel [7].

A sales argument is a document that organizes the arguments the sales force will use to present the product and address customer objections. The Feature-Advantage-Benefit method (FAB method [8]) is one of the most effective and practical methods in sales argument creation and preparation. Sales training programs frequently cite this method, and sales guides frequently refer to it [9]. However, subjectivity, irregularity, and fragmentation still mar the process of creating and updating sales arguments. It is a challenging task that requires considerable effort, time, and skills [10]. The salesperson's talent, experience, and skills are of significant importance.

The advent of Generative Artificial Intelligence (GAI) has brought us closer than ever before to mastering and fostering marketing functions. Particularly, in the sales funnel, GAI techniques intelligibly assist many stages, including making contact with prospects [11], recommending products [12], answering standard questions immediately and accurately [5], analyzing customer behaviors, identifying a suitable product and presenting it adequately [11- 14], managing negotiations with the buyer [12, 15], and providing emotional support for sales [11]. The release of powerful Large Language Models (LLMs) to the public has marked the beginning of a new era in GAI. In a global digital economy, LLMs have become one of the pillars of artificial intelligence. They refer to transformer language models obtained by scaling model size (hundreds of billions or more of parameters), pretraining corpus, and computation [16]. LLMs have exhibited notable capabilities in understanding natural language and solving complex tasks from multiple domains via text generation [17, 18]. Particularly, they have shown a remarkable emergent ability to engage in agent-like behavior [19]. This has led to an outburst of commercial efforts to create LLM-powered agents capable of completing tasks that require extensive interactive reasoning [20]. LLMs can create persuasive content equaling the effectiveness of humans in convincing users [21]. Besides, combining argumentative and persuasive communication methods with AI approaches satisfies consumer needs better [22, 23].

While LLMs have shown persuasive skills [24], there is a lack of using them in sales argument creation, and research on this topic remains limited. LLMs can make the sales argument creation process more efficient, faster, and cheaper by allowing the sales force to focus on other tasks, better manage blockages in the sales funnel, and make their sales argumentation more persuasive and relevant. Hence, LLMs can significantly improve sales argumentation and reassure sales professionals of their potential benefits in sales argument preparation. This motivates our work to assess LLMs in AI-assisted sales argument creation. To the best of our knowledge, this is the first work to study the capability of LLMs in crafting sales arguments. At the crossroads of the emergence of GAI and untapped potential for sales, this paper aims to evaluate the ability of LLMs to create accurate and effective sales arguments. Thus, our focused research question is, “Can LLMs generate coherent, persuasive, and relevant sales arguments from product data?” In particular, we evaluate the effectiveness of GPT-4 as one of the most capable general-purpose LLMs to date in the sales argument creation task. It has gained significant attention because it is in a position to create human-like text and understand the semantic meaning of natural language, demonstrating remarkable performance in various natural language processing tasks [25, 26]. Our study marks the first extensive performance analysis of GPT-4 in AI-assisted sales argument creation and preparation. It shows that LLMs can assist intelligibly in creating sales arguments. Our findings reveal that over 98% of the arguments generated by GPT-4 and judged by human experts are coherent and persuasive. Moreover, GPT-4 exhibits a remarkable precision rate of 91.53% in aligning these generated arguments with customer purchase motives such as security, comfort, money, novelty, etc. This finding should motivate future work to explore other LLMs and create intelligent LLM-based applications to automatically create and update sales arguments, allowing sales force to focus more on front-office tasks than back-office ones.

The remainder of this paper is structured as follows: Section 2 highlights the background and literature review. Section 3 describes the research methodology, encompassing data collection, pre-processing, the design of an efficient prompt, and evaluation guidelines. Section 4 presents the experimental results. Section 5 discusses the findings, elucidating their implications and delineating the inherent limitations of the research. Finally, Section 6 concludes the paper.

2. Background and literature review

2.1 Sales argument

In the sales funnel process, the sales force contacts customers, discovers their needs, presents an offer, deals with their objections, and concludes the sale [27]. Among these steps, “presenting offers” and “dealing with objections” are crucial since they require more argumentation skills and experience [28]. Indeed, effective sales argumentation cannot be improvised; it must be meticulously prepared by constructing a well-crafted sales argument. According to [7], the sales argument is a carefully crafted document highlighting product-specific selling points to better address the customer's needs and concerns and close the sale. It is a guide to structuring communication to influence the customer's decision-making process [29, 30]. Technically, a sales argument contains a variety of arguments designed to provide the sales force with precise knowledge of the features and qualities of a product, thereby enabling them to convince customers to make a purchase [31]. In this regard, it is an essential tool for the sales force in any successful sales operation, as it facilitates persuading the customer of the product's value.

Throughout an offer presentation, the sales force must convincingly explain the product's benefits by adapting and personalizing their message for each customer rather than using a standardized and scripted pitch [32]. This involves proposing an appropriate solution and justifying it with carefully selected arguments [9]. Customizing arguments to meet the needs and expectations of each customer significantly increases the likelihood of persuasion. In the post-presentation stage, customers often deliberate on the product's value and ability to meet their needs, leading them to raise objections and seek further clarification [10]. In these scenarios, effective sales arguments are crucial for overcoming objections and reassuring the customer.

Different sales techniques (or methods) have been developed to optimize and enhance the sales process stages. Common techniques employed in professional settings include PSBD (Problem-Solution-Benefits-Disadvantages), SOS (Situation-Objectives-Solution), AIDA (Attention-Interest-Desire-Acquisition), BANT (Budget-Authority-Necessity-Time), CAP (Characteristics-Advantages-Proof), and FAB (Features-Advantages-Benefits). Basically, these techniques are built on the art of communication and finding mutual benefit principles. Their choice depends on many factors, such as the product type, client (consumer or business), and activity sector. For example, BANT technique is frequently utilized in automobile dealerships. A more thorough treatment of sales techniques can be found in [33]. While PSBD, SOS, AIDA, and BANT encompass the entire sales process, CAP and FAB are particularly effective for developing sales arguments. FAB is the most recent and used method in various sectors, including retail, technology, and services [9]. Sales manuals frequently mention it, and many sales training programs still rely on it [9]. The sales force relies on the FAB method to increase their chances of a successful sale by adapting their communication to customers' needs and preferences [34]. In this regard, we have chosen to evaluate GPT-4's ability to generate sales arguments following this method. The sub-section below provides more details about it.

2.2 FAB method and purchase motives

2.2.1. FAB method

The authors in [7] argue that salespeople must structure and adapt the sales argument to arouse customers' interest and persuade them. This process requires a thorough understanding of the customer's needs and expectations, as well as an in-depth knowledge of the product or service features to effectively highlight their advantages and benefits. In other words, a compelling sales argument consists of successfully linking the product's selling points to the customer's needs. Customers are more likely to purchase when they consider that a product brings value and satisfies their needs. This is supported by the FAB method Fig. 1, which clearly communicates a product's features, advantages, and benefits to potential buyers and links them to consumer needs [35]. It explains the feature, what it does (the advantage), and how it benefits the customer (benefits) [8].

Features refer to the product's technical characteristics and properties, such as color, size, raw materials, guarantees, etc. Describing a product's characteristics answers the question, "What is it?" A feature is the extent to which the seller communicates information about the product's superior technical characteristics [36]. Typically, when used alone in the sales argumentation, features have little persuasive power, as buyers are interested in specific benefits rather than features [8].

The ***advantage*** is the improvement that the feature can bring to the customer. It focuses on how the feature will translate into tangible contributions and help the buyer [9]. Particularly, the competitive advantage of a product or service over its rivals [7] should be unraveled. For example, for a smartphone, a high-resolution screen (feature) improves visual clarity (advantage), a long battery life (feature) ensures continuous use (advantage), and a powerful processor (feature) enables smooth multitasking (advantage).

Benefits appeal to the customer's motives by answering the question, “What is in it for me?” They can be both practical, such as an investment, and psychological, such as an image of success [9]. The customer can derive personal or emotional gain from using the product or service. In other words, customers are interested in what the product will do

Received: July 5, 2024. Revised: July 31, 2024.

for them. Benefits communication involves revealing how the customer will benefit from purchasing the product and meeting its needs, rather than focusing on its features and benefits [36]. The benefits are the extra value an offer provides to the user [37]. It is a customer-focused sales process that aims to close sales of products satisfying customers' needs [38]. Considering the previous example of the smartphone product, a customer does not necessarily buy it for its high-resolution screen (feature) that improves visual clarity (advantage), but rather for the ease of use and eye protection (benefits). Similarly, the powerful processor (feature), which enables smooth multitasking (advantage), allows for saving time and improving the quality of the work (benefit). In sales argumentation, it is helpful to consider the benefits customers are looking for and then work backwards to determine the benefits and features of the corresponding product.

2.2.2. Purchase motives classification

One of the challenges facing marketers is accurately determining the benefits the customer will gain from using a product to meet their needs. The FAB method addresses this challenge by linking sales arguments with purchase motives [9]. Purchase motives (a.k.a. purchase motivations) are the reasons why customers decide to buy a particular product. For an effective sales argumentation, it is beneficial to explore these motives beforehand. Indeed, in the sales process, before presenting their offer, salespeople must first discover their customers' purchase motives by asking well-structured questions. This should lead to a classification of the purchase motives and needs expressed. Several methods are used to this end. [39] distinguish between two broad categories: rational and emotional. [7] proposes a classification based on Maslow's hierarchy of needs. Our study adopts the SONCAS classification method that groups consumers' purchase motivations around six motives: *Security*, *Vanity*, *Novelty*, *Comfort*, *Money*, *and Likeability* [40]. SONCAS is a French acronym for: *"Sécurité": Security, "Orgueil": Vanity, "Nouveauté": Novelty, "Confort": Comfort, "Argent": Money, "Sympathie": Likeability.* It was developed in 1993 by Jean-Denis Larradet, a sales executive at the French National Group for Automobile Training. The SONCAS classification provides a solid framework for understanding the key factors influencing customers' purchasing decisions, thereby increasing the chances of closing sales and developing long-term customer relationships [30]. In addition, it remains one of the most frequently cited classifications in sales manuals and the most adopted

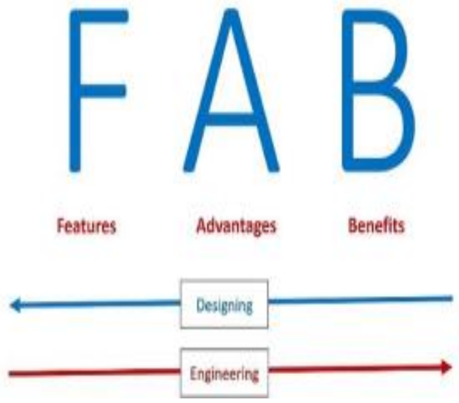

Figure.1 The FAB selling concept [37]

by marketing training organizations [31]. By grouping consumers' purchase motivations around the aforementioned six motives, the sales force can better target their argumentation strategies and propose solutions that meet the needs of their target audience. Indeed, the *security* motive relates to the need to feel safe and protected, which can motivate some consumers to favor reliable, quality products or services. The powerful motivator of *vanity* drives consumers to invest in luxury or high-end products, serving as a means to display their social status or enhance their self-esteem. *Novelty* refers to the allure of new and exciting experiences, which is a strong driver for some consumers, particularly those attracted to innovative and original products or at the forefront of technology. *Comfort* is a purchase motive for some consumers who value product functionality, quality, and comfort. They are looking for simple, practical solutions to simplify their daily lives. *Money* represents another motive for consumers who attach significant importance to the financial aspect of purchasing, hoping to save, get excellent value for money, or invest in sustainable products. Finally, *likeability* motivates some consumers who support brands or products that align with their beliefs and ethical concerns, including social and environmental ones**.** By grouping consumers' purchase motivations around these six motives, the sales force can better target their argumentation strategies and propose solutions that meet their target audience's needs.

2.3 Related work

This section reviews recent literature on the potential of LLMs in persuasion and argumentation in relation to AI-generated messages in various fields. We will pay particular attention to the marketing and sales domain, emphasizing the key studies and theories that have shaped our understanding of LLM's role in effective communication strategies, such as sales pitches, presentations, advertisements, etc.

2.3.1. LLMs in persuasion and argumentation

The use of LLMs in persuasion and argumentation is a relatively new topic, closely linked to the recent surge in the popularity of GAI's type. Thus, there has been a rapidly growing interest in this field over recent years, leading to the emergence of several new research projects.

Early research that focused on the persuasive capabilities of LLMs compared the arguments they generate with those of humans. By analyzing the features of arguments generated and transformed by LLM, researchers in [41] found that these arguments are logically sound, more factual, and rational. [21] showed comparable effects of persuasive messages written by GPT-3 or humans on several political issues. Similarly, [42] obtained comparable results on a set of controversial US-based partisan issues. [43] demonstrated that GPT-3 was capable of producing highly persuasive texts and arguments that closely resembled those of professional propagandists. In [44], the authors showed that GPT-3-generated messages were preferred over human-written ones in a pro-vaccination campaign. Besides, [45] studied the persuasive capabilities of LLMs through synthetic dialogues on climate change. They found that LLMs can indeed mimic human persuasion dynamics, with arguments incorporating knowledge, trust, status, and support that are considered most effective by both agents and humans. In recent research [24], the author has shown that the most advanced LLMs can use strategic thinking and language skills comparable to humans or very close to human levels. They are able to engage in discussions with humans and even outperform them in online strategy games involving negotiations [46-47]. [48] found that participants who debated GPT-4 with access to their personal information had 81.7% higher odds of increased agreement with their opponents compared to those who debated humans. They create a web-based platform where participants engage in short, multiple-round debates with a live opponent, and they analyze the effect of AI-driven persuasion in a controlled, harmless setting.

Overall, the aforementioned studies have demonstrated that LLMs excel at generating coherent and persuasive arguments within the political and social domains. They effectively mimic the dynamics of human persuasion and argumentation.

2.3.2. LLMs in persuasion and argumentation

In the field of marketing and sales, there is ongoing research studying the impact of AI-generated messages on customer persuasion. The advent of LLMs has accelerated this work.

In the field of marketing and sales, ongoing research is examining the impact of AI-generated messages on consumer persuasion. The advent of LLMs has significantly accelerated this area of research. A major study in this field defines AI-based persuasion as a symbolic process where messages created, augmented, or modified by AI entities are transmitted to human recipients to shape, reinforce, or modify their responses [49]. Based on the theory of construction levels, [50] explained how AI-led attempts at persuasion differ from human-led attempts. They demonstrated that AI-generated messages are more appropriate and effective when they exhibit the characteristics of a lower construction level. Another study concluded that humans, through a heuristic process, perceive AI-generated messages. For AI to be persuasive, it must provide highly relevant, easy-to-use, and accessible messages [49]. [44] suggested that while AI can be a valuable tool for generating public health messages, human supervision and intervention are essential. They presented best practices for evaluating the generative outcomes of LLMs, as well as guidelines for public health professionals on the use of AI systems in generating public health messages. Finally, [51] examined how LLMs can improve personalized persuasion. Their study proved that AI-generated personalized messages could improve the effectiveness of advertising messages. The researchers found that LLMs could "think" and react to external stimuli in a similar way to humans when generating psychologically tailored messages. These results suggest that LLMs could enable the automation and implementation of personalized persuasion. Furthermore, the study proves that AI-generated personalized messages can improve the effectiveness of advertising messages.

3. Materials and methods

This study aims to assess GPT-4's ability to generate sales arguments from technical documentation and sales materials, organizing them into features, benefits, and advantages, and connecting them to purchasing motives. This is a qualitative study based on an inductive approach with a realistic perspective. We deliberately chose an in-depth case study based on the IKEA Company [52], which is a global specialist in the production and retailing of furniture appliances and home accessories, for two reasons. First, the furniture product market is highly competitive [53], necessitating unique efforts and skills in sales argumentation to sell this type of product. Second, the company's sales materials (catalogues, brochures, and products sheets) are freely available on its website [54]. Fig. 2 shows the overall pipeline of our approach.

3.1 Data collection and preparation

We collected data from product sheets, catalogs, and brochures of 34 products in eight ranges on the IKEA company website [54]. These materials contain rich textual data, pdf files, images, figures, and diagrams in the English language. We only extracted textual data because our primary goal is to create sales arguments from textual descriptions of products using the FAB method. Then, we removed duplicates, extra white spaces, and special characters, and standardized the structure to ensure the data's quality, consistency, and reliability.

3.2 Model's deployment and prompt design

This research aims to exploit and evaluate the LLMs' persuasive ability [24] to assist in sales argument creation and optimization, with a particular focus on the widely recognized and capable OpenAI GPT-4 LLM. In this regard, we chose OpenAI gpt-4-0613, which is a snapshot of GPT-4 from June 13th, 2023 [55]. Its training data are up to September 2021. Its maximum context window length is 8,192 tokens, so each input data from our dataset fits well inside this context. We used the official OpenAI Chat Completions API to evaluate this model on sales argument creation within a zero-shot setting using an effective prompt depicted in Fig. 3. Fig. 4 shows its structure in the Chat Completions API format [56]. To control the randomness and repetition degree of GPT-4 generation, we set the *temperature* to 0.0 (higher values like 0.8 will make the completions more random, while lower values like 0.2 will make it more focused and deterministic), the *frequency_penalty* to 0.0, and the *presence_penalty* to 0.0.

3.3 Evaluation

To assess the results generated by GPT-4, we perform a human evaluation and a quantitative and descriptive analysis.

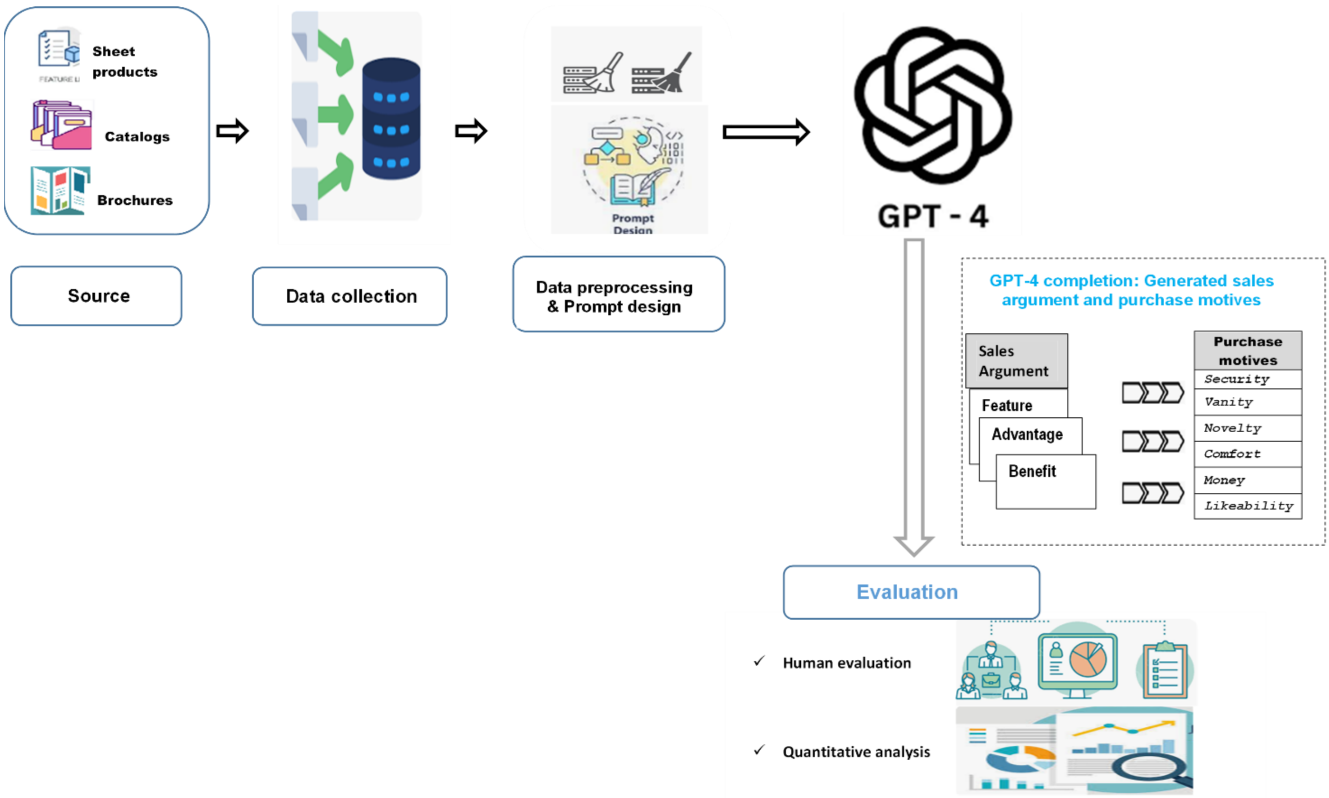

Figure. 2 The Proposed system pipeline

Received: July 5, 2024. Revised: July 31, 2024.

```
Prompt = """
     You are a seller expert, you will be provided with the technical and commercial data of
     a product line, and your task is to convert them to a list of persuasive sales
     arguments. Each argument must contain coherent Features, Advantages, and Benefits.

     For each argument, determine what consumers' purchase motives from the following list
     are linked to it.

     List of consumers' purchase motives: ["Security", "Vanity", "Novelty", "Comfort",
     "Money", "Likeability"]

     Data: ..........................
"""
```

Figure. 3 The designed prompt with input textual product data for sales arguments generation task

```
"messages": [
           { "role": "system",
             "content": [
                 {
                   "type": "text",
                   "text": " You are a seller expert, you will be provided with the technical
                   and commercial data of a product line, and your task is to convert them to a
                   list of persuasive sales arguments. Each argument must contain coherent
                   Features, Advantages, and Benefits.

                   For each argument, determine what consumers' purchase motives from the
                   following list are linked to it.

                   List of consumers' purchase motives: ["Security", "Vanity", "Novelty",
                   "Comfort", "Money", "Likeability"]"
                 }
             ]},
           {
             "role": "user",
             "content": [
               {"type": "text",
                "text": " ......Data................"
               }
             ]
           }
]
```

Figure. 4 The designed prompt in the Chat Completions API format (zero-shot prompt)

3.3.1. Design of the human evaluation

To understand the GPT-4 generative capabilities on sales arguments comprehensively, we will proceed with a thorough human evaluation inspired by studies in other fields [57-59]. We rely on human evaluation because, in our case, certain aspects of generated texts, such as coherence and persuasion, are difficult to evaluate using automatic evaluation metrics. Human evaluation is essential and unavoidable when assessing the quality of texts generated by machine learning models [60]. Such an evaluation requires domain knowledge, making it particularly challenging for non-experts. Below, we present the experts' profiles and the evaluation guidelines.

- Expert profile

Evaluating LLMs' argument-generating capabilities requires in-depth knowledge of sales argumentation. This competence constraint, the risk of informational redundancy [60], and theoretical saturation [61] compelled us to limit our sample to five experts, as summarized in Table 1. Furthermore, to avoid overburdening the evaluators, we assessed the arguments generated by GPT-4 for one randomly selected product from each range (Table 2). Sixty-one arguments are being evaluated.

- Evaluation guidelines

Previous literature on consumers' purchase intention [61-64] suggests that the quality of an argument can be assessed through various dimensions, such as coherence, accuracy, persuasiveness, relevance, timeliness, consistency, and adequacy.

In this research, we focused on three main criteria - coherence, persuasiveness, and relevance - to evaluate the quality of the generated sales arguments. We chose these criteria because of their common use by salespeople, their simplicity, and their suitability for human evaluation. Table 3 presents a brief description of coherence and persuasiveness criteria and guidelines for evaluators.

The relevance criterion evaluates an argument's ability to address the customer's needs, aligning with at least one of the customer's purchase motives:

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security, vanity, novelty, comfort, money, and likability. An argument may correspond to multiple purchase motives. We followed two particular steps to assess the relevance of the generated arguments. First, we asked the experts to select (i.e., annotate) the purchase motives that each argument, judged coherent and persuasive, aligns with. Second, we perform an automatic evaluation comparing the “true” motives (i.e., those correspond to the experts' agreement) and the ones generated by GPT-4.

Table 1. Profile of expert evaluators. QT: Qualified Teacher who has passed the high-level competitive exam on economic and management

	University degree	Major and field of activity	Experience years
Expert 1	Ph.D.	Marketing teacher at the ENCG National Business and Management School.	5 years
Expert 2	QT in marketing	Teacher of sales techniques at Advanced Technician's Certificate of Sales Management.	12 years
Expert 3	QT in marketing	Teacher of sales negotiation at Advanced Technician's Certificate of Sales Technology	9 years
Expert 4	Master's Degree in Marketing	Sales manager in a furniture and decoration retailer	10 years
Expert 5	Master's Degree in Marketing	Sales manager in a furniture and decoration retailer	15 years

Table 2. Number of arguments evaluated by product and range

Range	Product	Number of arguments
Bathroom	Bathroom showers	8
Bedroom	PAX & KOMPLEMENT	8
Children's IKEA	Children’s sleep	7
Business	Home, office and gaming chairs	10
KITCHEN	ENHET Kitchen system	6
Lighting and home electronics	ENEBY /VAPPEBY	6
Living Room	HAVSTA Storage series	7
Outdoor	Lounging and Relaxing	9
	TOTAL	61

Table 3. Criteria for argument quality (coherence and persuasiveness) and guidelines for evaluators

Criterion	**Short description**	**Guideline for evaluators**
Coherence	It measures the clear-cut relationship between the three parts composing an argument, namely feature, advantage, and benefit.	To evaluate the coherence of the generated argument, we asked expert evaluators to select one option from "Coherent", "Incoherent", or "Cannot be determined (CNBD)". The expert chose "Coherent" if the argument logically and systematically presented essential product information and highlighted the sequence of the product's features, its advantages, and its benefits for the customer. Otherwise, they chose "Incoherent". If the expert was in a deadlock situation and couldn't decide, they chose "CNBD".
Persuasiveness	Persuasiveness is measured by assessing whether the arguments presented are compelling and persuasive, as well as whether appropriate emotional appeals are used.	If the expert judged an argument as "Incoherent" or "CNBD", he would not evaluate its persuasiveness. To evaluate the persuasiveness of the generated argument, we asked expert evaluators to select one option from "Persuasive", "CNBD" or "Unpersuasive". The expert selects "Persuasive" if the sales argument can convince a potential customer to purchase the product. This ability primarily depends on effectively showcasing the product's features, advantages, and benefits in a persuasive manner. Otherwise, they select “Unpersuasive”. If the expert was in a deadlock situation and couldn't decide, they chose "CNBD".

3.3.2. Quantitative descriptive analysis

To further assess the effectiveness of the LLM's generative capability on sales argumentation, we conducted a quantitative analysis regarding products and range. We specifically selected the following indicators: number of generated arguments, number of generated purchase motives, dominant purchase motives, coverage rate, and deepening rate. We determine the coverage rate by dividing the number of purchase motives covered by their total number (6). A rate of 100% indicates that all purchase motives are addressed by at least one argument. In other words, salespeople will find at least one argument to address any perceived purchase motives in their clients. We determine the deepening rate by dividing the number of purchase motives generated at the product level by the total number of arguments. This calculation helps evaluate the range of options each sales argument provides to the sales force for targeting purchase motivation. For instance, a depth rate exceeding 200% indicates that the sales force will have at least two options to address a specific purchase motivation in their clients.

4. Results

In this section, we report the results of the generated sales argument using GPT-4. Our study included 34 products categorized into eight ranges (section 3.1). We generated 34 sales pitches, each containing multiple arguments structured according to the FAB model, and aligned with the corresponding purchasing motives. Table 4 shows an example of a generated sales argument for the

Table 4. Sales argument for Bathroom showers product generated using GPT-4. S: Security, V: Vanity, N: Novelty, C: Comfort, M: Money and L: Likeability

Arguments		Purchasing motives					
		S	V	N	C	M	L
Argument 1	**Feature**: The product provides a space for relaxation and comfort. **Advantage**: It allows for personal time and self-care. **Benefit**: Users can enjoy a private space to unwind and rejuvenate.				x		x
Argument 2	**Feature**: The product comes with clear care instructions. **Advantage**: It ensures the longevity of the product. **Benefit**: Users can maintain the product in good condition for a long time.				x	x	
Argument 3	**Feature**: The product comes with wall fittings and safety features. **Advantage**: It ensures safe and secure installation. **Benefit**: Users can have peace of mind knowing the product is installed securely.	x			x		
Argument 4	**Feature**: The product comes with a 10-year limited warranty for thermostatic faucets and a 3-year limited warranty for other parts. **Advantage**: It assures the product's quality and durability. **Benefit**: Users can have peace of mind knowing they are covered in case of any product defects.	x				x	
Argument 5	**Feature**: The product offers a variety of shower experiences. **Advantage**: It caters to different shower needs and preferences. **Benefit**: Users can enjoy a personalized shower experience.			x	x		x
Argument 6	**Feature**: The product is part of a complete range of bathroom accessories. **Advantage**: It allows for a coordinated bathroom style. **Benefit**: Users can enjoy stylish and harmonious bathroom decor.		x				x
Argument 7	**Feature**: The product comes with a range of services including delivery and assembly. **Advantage**: It provides convenience to the users. **Benefit**: Users can save time and effort in transporting and setting up the product.				x	x	
Argument 8	**Feature**: The product offers a click-and-collect service. **Advantage**: It provides flexibility and convenience in purchasing. **Benefit**: Users can easily purchase and collect the product at their convenience.				x	x	

"Bathroom Showers" product from the "Bathroom" range.

Below, we present the human evaluation results and a quantitative analysis.

4.1 Expert evaluation

4.1.1. Coherence

Table 5 presents the statistics from the expert judgments on the coherence of the generated arguments. In the agreement column, we calculate the number of arguments on which an agreement of judgment was reached by more than 60% of the experts (three experts out of five). Overall, the generated arguments demonstrate a high level of quality regarding the coherence criterion.

All five experts judged at least 85% of the arguments as "Coherent". Three of them considered more than 95% of the arguments as coherent. One expert confirmed the coherence of all the arguments. Out of 61 arguments, only one argument (argument 7 in table 4 for the "Bathroom Showers" product) did not obtain the 60% agreement of the experts in terms of coherence; one expert judged it "Incoherent", two were " CNBD ", and two considered it "Coherent".

Upon reviewing this particular generated argument, it became apparent that the issue stemmed from the vague and superficial description of its benefit, which was formulated as "It provides convenience to the users.". Three experts struggled to see how this benefit consistently aligned with the given product's feature: “The product comes with a range of services including delivery and assembly”.

4.1.2. Persuasiveness

Table 6 presents the statistics from the expert judgments on the persuasiveness of the generated arguments.

We remind that we instructed the experts not to judge the persuasiveness of arguments considered "Incoherent" or "CNBD" in terms of coherence. Consequently, the number of arguments judged differs from one expert to another. The last column, called agreement, shows the number of arguments on which an agreement of judgment was reached by more than 60% of the experts (three experts out of five).

At least 83% of the arguments evaluated (the number differs from one expert to another) are considered "Persuasive" by all the experts. For four of them, this rate exceeds 94%. One expert confirmed that all the arguments examined were persuasive.

Out of 60 coherent arguments that reached an agreement of judgment by more than 60% of the experts (three experts out of five), one argument did not achieve the 60% agreement of the experts in terms of persuasiveness. It is Argument 2, which is related to a product from the "Lighting and Home Electronics" range (see Table 7).

Upon reviewing this argument, it is considered "Unpersuasive" because it highlights the feature of "Bluetooth® speakers," which has become standard across all similar products. Consequently, it offers no unique advantage or benefit that would make the argument compelling.

Table 5. Human evaluation results of the generated sales arguments regarding the coherence criterion. CNBD: Cannot be determined

	Experts										**Experts Agreement (three experts out of five minimum)**	
	Expert 1		**Expert 2**		**Expert 3**		**Expert 4**		**Expert 5**			
	Nbre of arguments	**%**	**Nbre of arguments**	**%**	**Nbre of arguments**	**%**	**Nbre of arguments**	**%**	**Nbre of arguments**	**%**	**Nbre of arguments**	**%**
Coherent	52	85,3 %	60	98 %	53	86,9 %	61	100%	58	95,1 %	60	98,36 %
Incoherent	3	4,9 %	0	0%	2	3,3	0	0%	1	1,6%		
CNBD	6	9,8 %	1	2%	6	9,8 %	0	0%	2	3,3%		
Total	61	100 %	61	100 %	61	100 %	61	100%	61	100 %		

Table 6. Human evaluation results of the generated sales arguments regarding the persuasion criterion

	Experts										Experts Agreement (three experts out of five minimum)	
	Expert 1		Expert 2		Expert 3		Expert 4		Expert 5			
	Nbre of arguments	%	Nbre of arguments	%	Nbre of arguments	%	Nbre of arguments	%	Nbre of arguments	%	Nbre of arguments	%
Persuasive	43	83,7 %	59	98 %	45	94%	61	100%	55	95%	59	98,3%
Unpersuasive	0	0%	1	2%	1	2%	0	0%	0	0%	1	1,7%
CNBD	9	17,3 %	0	0%	3	6%	0	0%	3	5%	0	0%
Total	52	100 %	60	100 %	49	100%	61	100%	58	100 %		

Table 7. Argument 2 for the product Lighting and Home Electronics ENEBY /VAPPEB

Product	Argument
Lighting and home electronics: ENEBY /VAPPEBY	**Argument 2:** ENEBY 20 can be completed with a battery so that you can place it wherever you do not have a wall socket. With ENEBY Portable, you can listen to great music on the go.
	- **Feature**: Portable Bluetooth® speakers with battery option.
	- **Advantage**: Can be used anywhere, even without a wall socket.
	- **Benefit**: Enjoy your favourite music anywhere, anytime.

4.1.3. Relevance

The relevance criterion evaluates an argument's ability to address the customer's needs, aligning with at least one of the customer's purchase motives: security, vanity, novelty, comfort, money, and likability. We remind that to judge an argument's relevance, the expert must first consider it "Coherent" and "Persuasive". To assess the performance and efficacy of GPT-4 regarding the argument's relevance, we used Jaccard accuracy Eq. (1) and macro-precision Eq. (2).

For an argument x_i , Jaccard accuracy is determined through the Jaccard similarity coefficient between the predicted label sets $\tilde{y}_i$ and true label sets y_i.

$$Accuracy(f) = \frac{1}{N}\sum_{\boldsymbol{i=1}}^{N}\frac{|\tilde{y}_i \cap \boldsymbol{y_i}|}{|\tilde{y}_i \cup \boldsymbol{y_i}|} \quad (1)$$

Where y_i represents the set of true purchase motive labels for the argument x_i identified by the experts' agreement, $\tilde{y}_i$ represents the set of purchase motive labels predicted by GPT-4 for the argument x_i, and N denotes the total number of arguments.

Macro-precision (Equation (2)) is calculated as the precision averaged across all labels. It measures the models' performance per purchase motive (label).

$$Macro - Precision = \frac{1}{Q}\sum_{j=1}^{Q}\frac{TP_j}{TP_j+FP_j} \quad (2)$$

Where TP_j and FP_j denote, respectively, the total number of "True Positives" and "False Positives" considering the label λ_j as a binary class, and Q denotes the total number of labels, which is six (Security, Vanity, Novelty, Comfort, Money, and Likability).

GPT-4 achieves an impressive accuracy of 91.53%. It is very convincing in sales argument crafting, which is a challenging task requiring skilled sales force in argumentation and persuasiveness. This result shows the relevance of the generated arguments, demonstrating the capability of LLMs in sales argument creation.

Table 8 shows the effectiveness of GPT-4 regarding each purchase motive (label) in terms of macro-precision. The results demonstrated that the model achieved convincing performance for all purchase motives except "novelty". One contributing factor could be the knowledge held by the gpt-4-0613 snapshot, which is up to 2021. Most likely, the model

Table 8. Comparison of the performance results per Purchase Motive label.

Purchase Motive labels	Macro-Precision
Security	0.91
Vanity	0.92
Novelty	0.75
Comfort	0.95
Money	1.00
Likeability	1.00

Table 9. GPT-4 and Expert's agreement rate on argument relevance.

purchasing motives	GPT-4		Experts AGREEMENT (three experts out of five minimum)	
	Number of times generated	Ranking	Number of times selected	Ranking
Security	11	5	10	5
Vanity	12	4	12	4
Novelty	8	6	8	6
Comfort	41	1	41	1
Money	18	2	19	2
Likability	16	3	16	3

cannot detect the newness of features released after this date.

Table 9 displays statistics from GPT-4 and expert consensus regarding the purchase motives that an argument aligns with. Like the agreement reached by the human evaluators, GPT-4 ranked the purchase motives as follows: "Comfort" first, "Money" second, "Sympathy" third, "Vanity" fourth, "Security" fifth, and "Novelty" last. Thus, we noticed a significant correlation between human and GPT-4 results.

Among the eight products, the arguments generated by GPT-4 covered at least five of the six possible motives. Hence, GPT-4 gives sales force various choices for arguing their sales presentations and dealing with customers' objections.

4.2 Quantitative and descriptive analysis

Table 10 summarizes the descriptive statistics of data from 34 sales arguments generated for 34 products. Each row contains data related to a single sales argument per product.

- *Number of arguments generated:* GPT-4 generated 273, i.e., on average, 8 arguments per product and 34 arguments per range. These results will provide sales staff with more choices when defending their sales proposal and dealing with customer objections.
- *Number of purchasing motives generated:* in total, the six purchasing motives were generated 452 times. 41 times for "Security", 44 for "Vanity", 39 for "Novelty", 208 for "Comfort", 78 for "Money" and 42 for "Likability". The predominant purchase motive is the "Comfort" motive, supported by the company's product range and types, consisting of furniture and decorative items. The second one is "Money". These two findings are in line with IKEA's mission, as summarized in "To create a better life for as many people as possible," as defined by its founder, Ingvar Kamprad [52].
- *Coverage rate:* The arguments generated fully cover the six purchase motives for eight products (25%) and 5/6 for 22 products (68.75%). Therefore, the sales force has a high likelihood of addressing a customer's need, indicating the effectiveness of the developed sales arguments.
- *Sales argument depth:* For each product, the depth of the sales argument exceeds 100%. This means that the sales force finds, on average, at least one argument to address each purchase motive. For 15 products (47%), the sales argument depth is greater than or equal to 200%. As a result, the sales force has more options for addressing customer motives, justifying the ease of argumentation in sales proposals, and handling customer objections.

Table 11 summarizes the data from Table 10 by range, confirming the abovementioned general pattern. For example, the "Bathroom" range includes four products, with a total of 33 arguments generated, averaging eight arguments per product. All the purchasing motives were covered, with a predominance of "Comfort" and less emphasis on "Novelty".

Additionally, the sales argument depth is 161%, indicating at least one argument per purchase motive. This provides the sales force with more argumentation choices to better satisfy customers' or prospects' priorities regarding purchase motives. For instance, they could recommend the "BOAXEL Storage Solution" product (BED 01) for a comfortable and cost-effective bathroom solution.

Received: July 5, 2024. Revised: July 31, 2024.

Table 10. Descriptive statistics for 273 arguments generated for 34 products S: Security, V: Vanity, N: Novelty, C: Comfort, M: Money, and L: Likeability.

Range_Product	Product_ID	Number of generated arguments	Number of motive purchases covered	Number of times a motive purchase is generated						Predominant purchase motive	Coverage rate	Sales argument depth
				S	V	N	C	M	L			
Bathroom	BAT 01	8	6	2	1	1	6	4	3	C	1,00	213%
	BAT 02	10	6	1	2	1	8	3	5	C	1,00	200%
	BAT 03	8	4	1	1	0	5	2	0	C	0,67	113%
	BAT 04	7	2	0	1	0	6	0	0	C	0,33	100%
Bedroom	BED 01	10	5	1	3	1	8	5	0	C	0,83	180%
	BED 02	8	3	1	0	1	6	0	0	C	0,50	100%
	BED 03	6	3	1	0	1	4	0	0	C	0,50	100%
	BED 04	10	4	1	0	0	7	1	1	C	0,67	100%
	BED 05	5	5	1	1	2	4	1	0	C	0,83	180%
	BED 06	8	6	2	1	1	5	3	3	C	1,00	188%
	BED 07	9	3	0	1	1	7	0	0	C	0,50	100%
Children's IKEA	CHIL01	10	4	2	1	0	6	2	0	C	0,67	110%
	CHIL02	7	5	3	1	0	4	3	2	C	0,83	186%
	CHIL03	8	5	1	0	1	6	4	2	C	0,83	175%
	CHIL04	6	3	1	0	0	5	3	0	C	0,50	150%
Business	BUS 01	10	5	1	2	2	10	1	0	C	0,83	160%
	BUS 02	8	5	1	2	0	8	3	2	C	0,83	200%
	BUS 03	9	5	0	2	3	8	6	2	C	0,83	233%
KITCHEN	KIT 01	15	6	2	5	3	12	6	2	C	1,00	200%
	KIT 02	6	5	1	1	0	4	3	3	C	0,83	200%
	KIT 03	10	5	3	2	0	7	6	3	C	0,83	210%
	KIT 04	9	4	5	0	0	8	5	2	C	0,67	222%
Lighting & home electro.	LI 01	6	6	1	1	2	6	2	1	C	1,00	217%
	LI 02	7	6	1	1	3	7	1	1	C	1,00	200%
	LI 03	6	5	2	1	3	6	0	1	C	0,83	217%
	LI 04	10	1	0	0	0	10	0	0	C	0,17	100%
Living Room	LIV 01	6	6	1	1	1	1	1	1	None	1,00	100%
	LIV 02	7	5	1	1	1	3	1	0	C	0,83	100%
Outdoor	OUT 01	7	5	2	0	2	5	3	2	C	0,83	200%
	OUT 02	9	6	1	4	2	5	2	4	C	1,00	200%
	OUT 03	7	2	0	0	4	3	0	0	N	0,33	100%
	OUT 04	8	4	0	5	2	8	0	1	C	0,67	200%
	OUT 05	9	5	1	1	0	7	5	1	C	0,83	167%
	OUT 06	4	4	0	2	1	3	2	0	C	0,67	200%

 DOI: 10.22266/ijies2024.1031.59

Received: July 5, 2024. Revised: July 31, 2024.

Table 11. Descriptive statistics for 273 arguments by 8 ranges. S: Security, V: Vanity, N: Novelty, C: Comfort, M: Money, L: Likeability

Range_Product	Number of Product	Number of generated arguments	Number of motive purchases covered	Number of times a motive purchase is generated						Predominant purchase motive	Coverage rate	Sales argument depth
				S	V	N	C	M	L			
Bathroom	4	33	6	4	5	2	25	9	8	C	100%	161%
Bedroom	7	56	6	7	6	7	41	10	4	C	100%	134%
Children's IKEA	4	31	5	7	2	1	21	12	4	C	83%	152%
Business	3	27	6	2	6	5	26	10	4	C	100%	196%
KITCHEN	4	40	6	11	8	3	31	20	10	C	100%	208%
Lighting and home electronics	4	29	6	4	3	8	29	3	3	C	100%	172%
Living room	2	13	6	2	2	2	4	2	1	C	100%	100%
Outdoor	6	44	6	4	12	11	31	12	8	C	100%	177%

5. Discussion, implications, and limitations

In this study, we investigated the ability of GPT-4, as an LLM, to generate sales arguments. The findings are promising, demonstrating GPT-4's ability to produce coherent, persuasive, and relevant arguments.

Our results showed the efficacy of GPT-4 in a very challenging and time-consuming task that requires a skilled sales force. It can generate coherent, persuasive, and relevant arguments, allowing the sales force to save hours or even days. Therefore, companies can cut expenses during the sales process. This finding corroborates those of [65] and [66] who showed that the application of AI in marketing boosts sales productivity and lowers marketing expenses. In addition, by automating the preparation of sales arguments using LLMs, the sales force will focus on higher added-value tasks, such as customer relationship management and negotiation, thereby increasing the productivity and overall performance of the sales team. This aligns with [67], who found that AI-powered sales help sales teams automatically generate arguments and useful guidelines for high-quality presentations. This efficiency can lead to cost savings, potentially translating into lower prices for customers.

Moreover, our study yielded three key findings regarding the quality of the arguments generated using GPT-4. First, the expert evaluators deemed 98.36% of the generated arguments coherent, structured according to the FAB method as instructed in the prompt. This finding aligns with [24] research, where the authors found that LLMs generate arguments requiring greater cognitive effort due to their intricate grammatical and lexical constructions compared to human-created ones. Second, the experts judged over 98% of these coherent arguments to be persuasive. This result aligns with [68], who highlighted the effectiveness of the personalized messages generated by LLMs in achieving higher conversion and reservation rates when integrating these models and persuasive technologies within hotel recommender systems. Additionally, [24] noted a tendency for LLMs to incorporate moral language, utilizing a broader range of positive and negative moral foundations, which supports this result. Besides, [51] emphasized the rapid advancement of LLMs, like GPT-4, in bolstering the effectiveness and efficiency of persuasive strategies. This research suggests the potential for automation and scaling personalized persuasion techniques. The third key finding pertains to the relevance of arguments generated by GPT-4. Our results indicated an impressive accuracy (91.53%) in GPT-4's ability to align generated arguments with customer purchase motives categorized using the SONCAS method (security, vanity, novelty, comfort, money, likability). This aligns with [69], who demonstrated that LLMs perform comparably to humans in identifying convincing arguments across various tasks. In particular, they found that stacking predictions from multiple LLMs significantly improves persuasiveness performance, even surpassing human ability in predicting stances before and after debates. This capability of LLMs can be further enhanced through personalization by tailoring messages to individual characteristics, especially in direct conversations [47], which can increase relevance and engagement, potentially leading to higher agreement and persuasion.

This study highlighted a multifaceted research avenue with significant implications for marketing. LLMs have the potential to revolutionize persuasive communication strategies. They can dynamically craft advertising messages tailored to individual customer profiles based on data-driven insights. This approach, applicable to both the human sales force and virtual sales assistants (bots), leverages personal data and purchase history to enhance message relevance and potentially influence consumer behavior towards desired outcomes. Recently, authors [48] have demonstrated that participants exposed to GPT-4 arguments showed an 81.7% agreement rate in debate conversations when GPT-4 had access to their personal information. However, alongside this potential, the ethical ramifications and societal impact of employing AI-powered persuasion require further investigation. It is crucial to understand the implications of promoting divisive or harmful content through AI-generated persuasive language. LLMs could be more effective and provide pedagogical support for sales argumentation training.

This research contributes meaningfully to the understanding of LLM capabilities in creating sales arguments, acknowledging the presence of inherent limitations. It exclusively utilizes data from products and categories within the furniture, appliances, and home accessories domain. This represents a constraint on generalizing our findings, thereby impeding the extension of conclusions to alternative industries and product/service categories. Future investigations should strive to examine the transferability of these findings within diverse contexts. In addition, we have evaluated GPT-4's capabilities to generate sales arguments according to the FAB method. We should conduct additional experiments with different persuasive models to gain deeper insights and enrich our understanding of their capabilities. Lastly, a comparative analysis with other LLMs allows us to further understand the emergent abilities related to sales argument generation across a spectrum of scenarios. Subsequent research endeavors would benefit from incorporating multiple LLMs to facilitate a comparative evaluation of their effectiveness in this domain.

6. Conclusion

This research investigated the capabilities of LLMs for creating sales arguments. It demonstrated that GPT-4, recognized as one of the most capable LLMs to date, possesses a notable ability to generate well-structured, coherent, persuasive, and relevant sales arguments from real-world product data. The experimental results showed that over 98% of the generated arguments are coherent and persuasive. Besides, the alignment of these arguments with customers' purchase motives achieved 91.53% in terms of accuracy. Therefore, LLMs will make a significant advance in the sales function, offering a powerful tool for creating sales arguments quickly and cost-effectively. These advantages are an asset for companies looking to improve their sales strategies. Furthermore, the potential of LLMs will improve commercial argumentation creation and deployment, paving the way for more personalized and effective marketing communications in the digital era. These insights are critically important, as they not only highlight the potential contributions of LLMs to sales argumentation, but also provide guidelines for future research. These include comparing the generation capabilities of various LLMs and assessing the impact of feeding them with customer data to enhance their persuasiveness in sales argument creation.

However, the deployment of LLMs in creating sales arguments raises important ethical considerations, especially the need to govern the use of these GAI models in sales argumentation. Businesses must navigate concerns regarding the authenticity and transparency of AI-generated content to maintain consumer trust and adhere to regulatory standards.

Future research should focus on refining GPT-4's performance in complex scenarios and developing frameworks to mitigate ethical risks. Longitudinal studies assessing the impact of AI-generated sales arguments on consumer behavior and business outcomes will provide valuable insights into the technology's long-term efficacy. Exploring the use of GPT-4 in conjunction with other company tools, such as customer relationship management systems, could further enhance its utility in the marketing domain.

Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

Conceptualization, methodology, software, validation, formal analysis, M. Elhissoufi, E. Nfaoui, and L. Alla; investigation, resources, data curation, M. Elhissoufi, E. Nfaoui, L. Alla, and J. Elghalfiki; writing—original draft preparation, writing—review and editing, M. Elhissoufi, E. Nfaoui, and L. Alla; visualization, M. Elhissoufi, E. Nfaoui, L. Alla, and J. Elghalfiki; supervision, project administration, E. Nfaoui, L. Alla.

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